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A New Type of Neural Fuzzy System and its Application in Automatic Fire Detection

Abstract

A new type of neural fuzzy system is proposed in this paper. With the advantages of network learning, this system solved the problem of defining training data set by human's experiential knowledge, which was impossible to be solved with conventional fuzzy principle. The construction and learning algorithm of this system, and extraction of inferential rules are discussed. Theoretical analysis and the application in automatic fire detection demonstrated that the new neural fuzzy system could be effectively used in the areas where inferential rules are changeable and difficult to be extracted.

1. Introduction

Fuzzy system based on fuzzy logic simulates human's comprehensive inference and judgement and solve the problems of fuzzy information processing which is hard to be solved by normal methods. Fuzzy system has been widely used in industrial and domestic intelligent products. But the further development of fuzzy technique has been puzzled by the problem of extraction of inferential rules. The over changed and innumerable applications of inferential rules cannot be worked out through expert's experiences and knowledge based inductive and trial-and-error methods.

Artificial neural network which features nonlinear and large scale parallel processing, has recently made attractive progress. Simulating biological neural network makes its strong ability of adaptive learning, tolerance and robustness, and it is good in association, synthesis and dissemination. Combined with neural network, the fuzzy system can overcome the shortcomings of normal fuzzy system and improve the ability of learning and expression. The research work has made great progress since the middle of the 1980s and many combinations of fuzzy system with neural network have been introduced [1][2][3]. These combinations can be divided into two types.

One is the type of structure equivalence [3] where all the nodes and parameters have specified meanings corresponding to membership function and inference procedure of fuzzy system, and they can even transform each other. The structure equivalence system has therefore been widely used. The problem of this type of fuzzy system is that the number of inferential rules depends on the structure of network. It becomes unsuitable when the number of inferential rule is changeable.

Another form is the combination of network learning [2], where all or part of the fuzzy system's fuzzification, linguistical rules, inference and defuzzification are realized with neural network. The physical meanings of neural network are not clear. Therefore the extraction of linguistical rules and the inference procedure are opaque and hard to understand. Particularly when linguistical rules and inference procedure are realized with neural network, and the inputs and outputs of the system are all fuzzy values, it is impossible to define the training data set by experiential knowledge. This has been the main problem hindering this type of fuzzy system from practical application.

A new combination system featuring network learning is proposed in this paper. The system, with the advantages of network learning system, solved the task of defining the training data set by human's experiential knowledge therefore could be used in those fuzzy systems where the number of inferential rules is of infinity. The extraction of inferential rules is also discussed in this paper.

2. The system's construction
A typical fuzzy system mainly includes three parts: fuzzification, fuzzy logic inference and linguistical rules, and defuzzification. If linguistical rules are hard to extract or the number of the rules is large or even infinite, the system cannot be realized by normal fuzzy method. A multi-layer feed forward neural network can be used to store the linguistical rules and the inference of fuzzy logic. The network is a typical BP neural network with three layers (see figure 1), where the inputs and outputs are fuzzy values
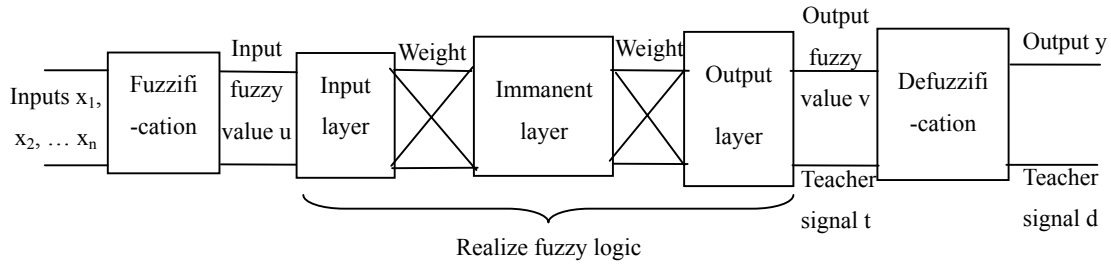
Fig. 1 A fuzzy system with inferential rules realized by a three-layer BP network

(respectively u and v), the immanent layer of the network is used to realize the inference of fuzzy logic, and the weight between each layer are used to store the linguistical rules. The network has, in fact, the form of network learning [2].

The kernel operation of realization of BP network is the procedure of learning. The output of the three-layer BP network is fuzzy value v rather than the final output y of the whole fuzzy system. So the teacher signal t is difficult to define. In general, experiential knowledge can be used to define the teacher signal d for final output y. It seems that deducing the teacher signal t from the teacher signal d would solve the problem. Unfortunately this cannot be realized. A typical procedure of defuzzification, for example the gravity center method is not a reversible procedure. The teacher signal d can be deduced from the teacher signal t, while the teacher signal t cannot be deduced from d. This is why the combination of network learning has difficulty in application.

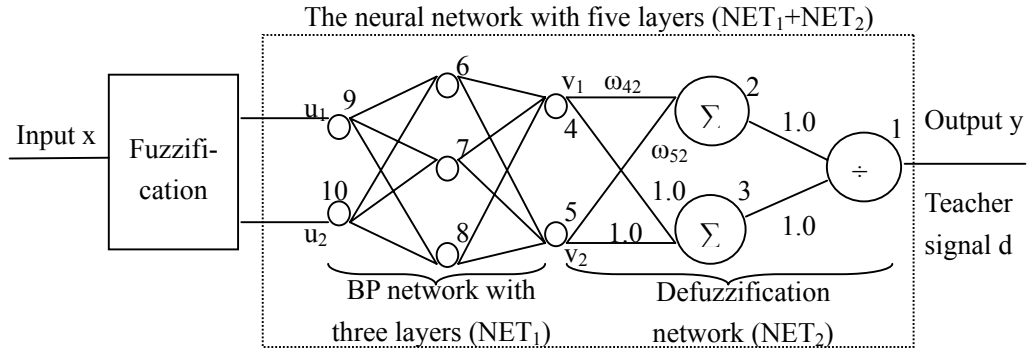The neural network with five layers (NET$_1$+NET$_2$)

Fig. 2 A typical and simple neural fuzzy system

The system structure can be improved. According to the principle of structure equivalence, the part of defuzzification can be realized by a special neural network (see NET$_2$ in Figure 2). And the network (NET$_2$) can also be combined with a BP network of three layers (NET$_1$) to form a larger neural network, which can be trained by the data set (u, d). The fuzzy value u can be transformed from input values x$_i$ through fuzzification. The fuzzification procedure can be done by directly training the BP network or by extracting the membership function through trial-and-error method. The whole system consists of two parts (see figure 2). One is the part of fuzzification. Another one is the five-layer neural network used to realize fuzzy logical rule inference and defuzzification. The system can be named as neural fuzzy system, and can also be regarded as a fuzzy neural network.

3. Algorithm of leaning

Suppose that the neural fuzzy system (see figure 2) has a single input x and a single output y. The fuzzy values u$_1$ and u$_2$ are the fuzzification results of input signal x. The system output y is the defuzzification result of fuzzy values v$_1$ and v$_2$ that are the result

of fuzzy logical inference. And the immanent layer of BP neural network has three neurons.

The fuzzification procedure has no relationship with the learning and application of the follow up network whatever fuzzification method is used.

For the algorithm, only the section from fuzzy values u1 and u2 to the system output y needs to be considered. Inside this section is the five layer neural network including three-layer BP network and two layers of structure equivalence network (see the dotted part of figure 2). For this combined neural network, the conventional error back-propagation algorithm should be effective. The problem is that the errors of neuron 4 and 5 are difficult to be estimated. With reference to the inferential procedure of BP algorithm, the learning algorithm of the five layers neural network can be inducted from the principle of maximum gradient reducing[3].

Suppose the output of neuron i is O_i (i=1,2…10), the weighted sum of inputs is net_i (i=1,2…10), and w_{ij} is the connecting weight of neuron i and j, among which the value of w_{21}, w_{31}, w_{43}, w_{53} is constantly 1.0. The neurons "$\sum$" and "$\div$" are different from the normal in that: the "$\sum$" are add units, their outputs are the sum of all inputs, i.e. their excitation function is f(net)=net; the "$\div$" is a division unit with the output of quotient for two inputs. The mean-square error of the system is

$$E = \frac{1}{2}(d - o_1)^2 , \qquad\qquad (1)$$

where d – teacher signal.

Two weights w_{42} and w_{52} of the neural network need to be adjusted. And others are unchangeable:

$$O_1 = \frac{O_2}{O_3}, \; O_2 = w_{42}O_4 + w_{52}O_5, \; O_3 = O_4 + O_5 . \qquad\qquad (2)$$

We have $\Delta w_{42} = -\eta \frac{\partial E}{\partial w_{42}} = \eta \cdot (d - O_1) \cdot \frac{O_4}{O_3}$, $\Delta w_{52} = -\eta \frac{\partial E}{\partial w_{52}} = \eta \cdot (d - O_1) \cdot \frac{O_5}{O_3}$. (3)

With generalized δ rule, a δ_k can be defined as $\delta_2 = (d - O_1) \cdot \frac{1}{O_3}$. (4)

In fact the above result can be worked out by using the procedure of generalized δ rule.

That means $\delta_2 = -\dfrac{\partial E}{\partial net_2}$. Because neuron 2 is an add unit, the result of the procedure is

the same as formula 4. Although the weight of w_{43}, w_{53} are fixed, the δ of neuron 3 can still be calculated:

$$\delta_3 = -\frac{\partial E}{\partial net_3} = (d - O_1) \cdot \left(-\frac{O_2}{O_3^2} \right). \qquad (5)$$

The δ values of neuron 4 and 5 are:

$$\delta_4 = (w_{42}\delta_2 + \delta_3) \cdot f_4'(net_4), \; \delta_5 = (w_{52}\delta_2 + \delta_3) \cdot f_5'(net_5). \qquad (6)$$

If $f(\cdot)$ is a sigmoid function, then

$$\delta_4 = O_4 \cdot (1 - O_4) \cdot (w_{42}\delta_2 + \delta_3), \; \delta_5 = O_5 \cdot (1 - O_5) \cdot (w_{52}\delta_2 + \delta_3), \qquad (7)$$

and $\Delta w_{j4} = \eta \delta_4 O_j$, $\Delta w_{j5} = \eta \delta_5 O_j$ (j=6, 7, 8). $\qquad (8)$

These are formal results because δ_3 has no actual significance, but the results are the same form as the ones of using the method of maximum gradient reducing, the derivation procedure of which is omitted in this paper. The purpose of using the similar deducing procedure as the general δ rule uses is to make calculation and remembrance easy. The meaning of δ_3 is clearly different from other δ values.

Since δ_4 and δ_5 have been obtained, the five layers neural network can now be trained directly by using the generalized δ rule. And the conventional BP algorithm can be applied to learning procedure of the new network. The kernel procedure of learning algorithm based on the algorithm of maximum gradient reducing is still the back propagation of error. The algorithm has the same form as the BP algorithm has, except that the deducing method of δ values of special neuron is different.

4. Application in automatic fire detection

The neural fuzzy system was applied to signal processing of an optical smoke and heat combined detector. The block diagram of the experimental system is similar to figure 2. There is an operation of characteristic extraction before fuzzification. The system input signals are smoke and temperature. Two characteristics are extracted from each signal: signal amplitude and signal rising trend [4][5][8]. Let S and T be the signals of smoke and temperature, S_b and T_b be the base values of smoke and temperature. The characteristics of amplitude are $S_\Delta = S - S_b$ for smoke and $T_\Delta = T - T_b$ for temperature. The signal

trends are deduced with the algorithm of exclusive trend expressed in documents [4] [5][8].

The function of sgn1 and sgn2 are redefined as follows:

$$\text{sgn}1(x) = \begin{cases} 1 & x > s \\ 0 & x \le s \end{cases}, \quad \text{sgn}2(x) = \begin{cases} 1 & x > 1 \\ 0 & x \le 1 \end{cases} \tag{9}$$

Where x - input variables for the fuzzification (S_Δ, T_Δ and their trends), and s = $0.25T_b$ or $0.25S_b$. The window length of exclusive trend algorithm is 10 seconds. The inferential procedure is realized by the fixed membership function determined by the method of trial and error. Each input x_i has two fuzzy values: big and small. The three layers of BP neural network have 8, 10 and 4 neurons for the first, second and third layer. The outputs of the system are the probability of fire and the probability of smoulder.

Based on the data analysis of test fires of European standard EN54-9, 12 sets of training data sample corresponding to inferential rules were delivered. Some of the training data are given in table 1. By using the above learning algorithm, the system error was less than 0.0001 after 8180 times of iterative operation.

Table 1 Some training data samples

NO.	T_Δ	T_τ	S_Δ	S_τ	F	HF
1	0.70	0.45	0	0	0.80	0.05
3	0	0	0.60	0.50	0.60	0.65
5	0.55	0.45	0.05	0.10	0.60	0.20
11	0.70	0.45	0.95	0	0.80	0.45

Notes:

T_Δ – Amplitude characteristic of temperature S_Δ – Amplitude characteristic of smoke

T_τ – Trend of T_Δ S_τ – Trend of S_Δ

F – Probability of fire   HF – Probability of smouldering fire

We used the data of seven test fires of EN54-9 collected in a standard fire laboratory to simulate fire, and the data of no-fire and smoking collected in the standard fire laboratory to simulate no-fire and smoking situations. Experimental results are shown in table 2. The system responded to fires effectively and did not respond to deceptive

phenomena caused by, for example, smoking, while the response time was shorter. The neural fuzzy system was of benefit to respond to incipient fire and to reduce the rate of false alarm effectively.

Table 2 Responses to fire, no fire and smoking situations

	TF1	TF2	TF3	TF4	TF5	TF6	TF7	No-fire	Cigarette smoke
Low threshold	260s	392s	397s	85s	93s	219s	107s	3 times of false alarm	False alarm
High threshold	308s	436s	624s	94s	120s	254s	175s	1 time of false alarm	No false alarm
Neural fuzzy system	252s	387s	365s	67s	79s	157s	99s	No false alarm	No false alarm

Note: The response time in this table is the time from the start point of test fire to the alarm point, in terms of second (s). "No-fire" is the data collected in a standard laboratory for about 24 hours, for reference only. "Low threshold" and "High threshold" are the data given by conventional detector working at high and low sensitivity respectively.

5. Conclusions

A new type of neural fuzzy system is constructed in this paper. Linguistical rules, fuzzy logic inference and defuzzification of the system are realized by using a neural network of five layers. And a learning algorithm similar to the BP algorithm is provided for training the network. The system not only has the advantages of network learning, but also overcomes the shortcomings that its training data model of inferential rules cannot be obtained by using experiences and knowledge. The new system has strong adaptability and can effectively solve the problem of extraction of inferential rules in many applications.

There was no effective method of fire signal characteristic extraction used for discrimination between fire and non-fire. So it has been difficult to find all inferential rules of automatic fire detection.

The new type of neural fuzzy system was applied to an experimental system of automatic fire detection. With this new neural fuzzy system, effective inferential rules can be obtained from a small amount of training data model. These rules, which are suitable for various types of fire and more effective than those obtained by conventional method, are implied into the weights of the neural network. Experimental result shows that the system can reduce false alarm effectively while does not fail to alert, and the alarm time becomes shorter. With this new system, the inferential rules can be automatically extracted for individual applications. The shortcoming that the inferential rules of existed fuzzy system are unchangeable can be overcome.

The system has stronger adaptive learning ability. In real field condition, the probability of real fire would be about zero during long time of observation. If the system reports an alarm during this period, it must be a false alarm and the data can be used as training data model for the system's learning. Then the system could obtain the inferential rules of reducing false alarm after learning. Theoretical analysis and experiments demonstrate that this new neural fuzzy system discussed in this paper can be effectively used in the applications where inferential rules are changeable and difficult to be extracted.

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